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INTRA-INDUSTRY PROFITABILITY DIFFERENCES IN U.S. MANUFACTURING: 1953-1983

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ABSTRACT

Over the period 1953-83, twelve accounting measures of profitability, which are not on average highly correlated, imply measures of the profitability advantage of large firms that move closely together. All twelve measures decline significantly and substantially over this entire period; there is no acceleration in the 1970's. All measures move counter-cyclically. Together with recent work on the dynamics of the inter-industry concentration-profitability relation, these results point to the existence of important pro-cyclical industry-level changes in the strength of the concentration-profitability relation.

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1. Introduction

This essay is an exploration of territory that lies between areas that have been investigated by two related lines of empirical research in industrial organization. Both lines are concerned with the relation between industry concentration and industry-average profitability. The first considers how and to what extent this relation reflects systematic *intra-industry* profitability differences; the second examines *changes* in the inter-industry concentration-profitability relation over time.[1] The goals of the present study are to see if there are systematic *changes* in *intra-industry* profitability differences over time in U.S. manufacturing and, if there are, to see how the pattern of changes relates to the results appearing in these two literatures.

The first line of research dates from the work of Demsetz (1973, 1974). Demsetz noted that firms that are relatively efficient in production or marketing tend to grow at the expense of their rivals and argued that industries accordingly become highly concentrated when efficiency differences among rival sellers are great. He went on to contend that the frequently-observed and much-discussed correlation between industry concentration and industry-average profitability might well reflect only the higher efficiency rents earned by leading firms in concentrated industries, rather than any relation between concentration and collusion. A simple algebraic version of this argument will be useful in what follows.

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[1]Both strands of research are discussed in more detail in Schmalensee (forthcoming); see also Schmalensee (1987) on the second. The results reported here also have implications for the relation between profitability and absolute firm size studied by Hall and Weiss (1967) and subsequent authors. The mixed results obtained in this cross-section literature (see Schmalensee (forthcoming)) may reflect, at least in part, intertemporal changes of the sort reported here.

Under Cournot rivalry (and a number of other behavioral assumptions), long-run equilibrium under constant returns to scale when firms' unit costs differ involve intra-industry relations of the following form (see Schmalensee (1987) and the references cited there for details):

$$r_{if} = \rho_i + \delta_i(s_{if}), \tag{1}$$

where r_{if} is the rate of return of firm f in industry i, s_{if} is its market share, and ρ_i and δ_i are industry-specific non-negative constants. In long-run equilibrium, more efficient firms have higher values of both r and s. The parameter ρ_i can be interpreted as the expected profitability of very small firms in industry i. Taking the share-weighted average of the r_{if}, we obtain the industry-average rate of return:

$$r_i = \rho_i + \delta_i(H_i), \tag{2}$$

where H_i is the H-index of concentration (the sum of squared market shares) for industry i.

Demsetz' view can be summarized (or perhaps caricatured) by the assertions that the ρ_i vary little across industries and that the δ_i are generally positive and large. It then follows that r_i and H_i will be correlated in cross-section because of intra-industry differences alone. The standard alternative interpretation of this correlation, associated with the work of Joe Bain (1951), can be similarly summarized by the assertions that the second term in (2) is relatively unimportant and that the ρ_i are on average higher in concentrated industries because concentration facilitates collusion.

I recently (Schmalensee 1987) attempted to distinguish between these two views using U.S. Internal Revenue Service minor industries for 1963 and 1972

and measuring profitability as the ratio of pre-tax profits plus interest payments to total assets. I estimated a variant of equation (1) with intra-industry data and found, among other things, that in most industries δ_i declined between these years, while the changes in ρ_i were negatively correlated with concentration.

The second strand of research may perhaps have begun with the observation of Leonard Weiss (1974) that the strength of the inter-industry relation between concentration and profitability seemed to vary systematically over time. Domowitz, Hubbard, and Petersen (1986a, 1986b, 1987) -- DHP for short -- have recently studied this variation using a panel data set based on the U.S. Census of Manufactures and covering the period 1958-81. They find that over this period the relation between industry-level price-cost margins and industry concentration (with the industry capital-output ratio included as a control) weakened dramatically and that margins were more strongly pro-cyclical in more concentrated industries.

My (1987) results suggest that those of DHP might in part reflect changes in intra-industry profitability differences -- the δ_i -- rather than simply changes in inter-industry behavioral differences -- reflected in the correlation between the ρ_i and concentration. But I only studied two years, and these could be outliers.[2] In order to see if there is in fact systematic

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[2]Demsetz (1974) has suggested that 1963 was an outlier in relevant dimensions, for instance, and some have argued that the Phase II price controls in effect in 1972 had a stronger impact on large firms than on their smaller rivals. This second argument is evaluated in Schmalensee (1987). It is perhaps worth noting that 1972 is not an obvious outlier in any of the analysis reported here.

variation in intra-industry profitability differences over time, it is essential to work with a relatively large set of years.

The data employed in this study and the methods used to analyze them are discussed in the next Section. As that discussion attempts to indicate, my orientation here is exploratory and descriptive. I attempt to draw a rough map of some unexplored territory, in part to see if it might be interesting for others to return, not to do definitive cartography or to test structural hypotheses.

The results obtained are reported in Sections 3 and 4. The suggest that further exploration of this territory would indeed be worthwhile. Section 3 summarizes the annual estimates of the average profitability advantage of large firms. These estimates provide strong evidence that intra-industry profitability relations have in fact changed systematically.

Section 4 analyzes the secular and cyclical components of these changes. The intra-industry advantage of large firms deteriorates substantially over the sample period. This parallels the secular deterioration in the inter-industry relation between concentration and profitability reported by DHP. But, while DHP find that the concentration-profitability relation tends to be strongest at cyclical peaks, the profitability advantage of large firms over their smaller rivals tends to be strongest at cyclical troughs. Section 5 briefly considers some implications of these findings.

2. Data and Methods

This study is based on data on manufacturing industries taken from the U.S. Internal Revenue Service *Statistics of Income: Corporations* for the years 1953-83. This data source not only permits the use of a long sample period, it

also provides comprehensive coverage in each year. Only partnerships and proprietorships are excluded from the IRS data, and they account for a tiny fraction of manufacturing activity.[3]

But the IRS data are not ideal. To obtain coverage of the long sample period necessary to show intertemporal patterns clearly, the database had to be assembled by hand. And, as I argue just below, the limitations of accounting data made it necessary to work with a large number of profitability measures. Given these requirements, I elected to bound the cost of this exploratory study by working primarily with aggregate data on all manufacturing corporations and adjusting for inter-industry differences, rather than carrying out estimation at the industry level. This strategy also facilitated summarization of sector-wide intertemporal patterns.

Accounting Biases and Profitability Measures Perhaps the most obvious shortcoming of these accounting data, in light of the critiques of Benston (1985), Fisher and McGowan (1985), and others, is that they can provide at best noisy measures of real, economic profitability. And since one cannot track individual firms over time in the published IRS data, one cannot even attempt to correct for accounting biases.

I deal with this difficulty here by employing the 12 different measures of profitability described in Table 1. Many of these measures have appeared in the literature previously. (For instance, Schmalensee (1987) uses r_4, and the measure used by DHP is closest to r_{12}, though their data exclude advertising, R&D, and other corporate-level costs.) These measures differ in their

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[3]In 1983, for instance, corporations accounted for 98.8% of business receipts and 99.6% of net income in manufacturing. (Source: *Statistical Abstract of the United States, 1987*, Table 853.)

treatment of income taxes, leverage, and depreciable assets -- all potential sources of distortion in comparisons between large and small firms. Each of r_1 -- r_{12} has weaknesses as an estimator of firm profitability at any instant, both in principle and, because of accounting biases, in practice. But the effects of the more obvious accounting biases vary considerably among them. In particular, discrepancies between accounting and economic depreciation have diverse effects on these measures, as do differences in effective tax rates and in debt/equity ratios.

These 12 measures give rather different pictures of the evolution of the average profitability of manufacturing firms. As Table 1 indicates, 7 of the 12 decrease over time on average, and 5 increase. (Five of the 7 negative regression coefficients are significant at the 5% level, as are 4 of the positive coefficients.) Five of the 6 r's based on before-tax profits fall over time, while four of the 6 r's based on after-tax profits rise. Moreover, the r's have substantially different coefficients of variation around the sample means and around the trend regressions. Since the statistics in Table 1 refer to all-manufacturing averages, it follows that even sharper differences in the trends of these measures exist at the industry and firm levels.

Table 2 provides correlations among the levels of the 12 measures of average manufacturing profitability and among the deviations of these measures from their trends. The relatively low correlations above the diagonal mainly reflect the divergent trends presented in Table 1. The higher correlations below the diagonal indicate that these measures tend to move together over the business cycle. But there is evidence of diversity here, too; in particular, deviations of r_{11} and r_{12} from their trends are not highly correlated with the other de-trended measures of manufacturing profitability. This parallels the

finding by Liebowitz (1982) and others that price-cost margins are not highly correlated with other measures of profitability in cross-section.

In light of this diversity and my focus here on changes in cross-section relations over time, it seems plausible to suppose that results that are robust across all 12 profitability measures reflect changes in relations involving economic profitability. Even if this supposition can be shown to be false, this study has implications for the interpretation of the vast literature that employs a variety of accounting profitability measures. For that purpose, differences among the 12 measures are of some interest.

Size-Class Analysis A second important shortcoming of the IRS data is that they contain only totals for sets of firms grouped by the size of their total assets. Firms with zero total assets were excluded from the analysis. The number of usable size classes then ranged from 7 (in 1962) to 14 (in 1954-60 and 1963). The mean and median number of classes was 12.[4]

As Daskin (1983) shows clearly, without strong assumptions about firm size distributions within size classes, one can consistently estimate only models that are linear in the firm-level variables that are summed to obtain size-class totals. In Schmalensee (1987) assumptions about intra-class distributions were used to develop estimators of a variant of equation (1), which is quadratic in the relevant firm-level variables. Since the orientation of the present study is descriptive, it seemed better to minimize the role of untestable assumptions and to work instead with a simple linear model of the determination of firm-level profitability:

$$\Pi_{cf} = \alpha + \beta S_{cf} + \epsilon_{cf}, \tag{3}$$

[4]Regression analyses turned up no evidence that changes in the number of size classes significantly affected the estimates reported below.

where Π_{cf} is the profit of the f^{th} firm in size class c (measured by one of Π_1 -- Π_6), S_{cf} is its size (measured by either total assets or business receipts), and ϵ_{cf} is a disturbance term discussed further below. Neglecting the disturbance term for the moment, we can divide through by S_{cf} to obtain

$$r_{cf} = \alpha(1/S_{cf}) + \beta, \tag{4}$$

where $r_{cf} = \Pi_{cf}/S_{cf}$ is a measure of firm profitability (corresponding to one of r_1 -- r_{12}).

It is important to recognize explicitly that equation (4) cannot be derived from the equilibrium relation given by equation (1) or from any other asymmetric oligopoly model of which I am aware. Nor is equation (4) intrinsically appealing as a structural model, particularly for very small firms. But estimation of its parameters should reveal substantial changes over time in those of the underlying structural relations between firm size and profitability. To facilitate interpretation I will assume that those structural relations are given by equations (1) and (2).

Examination of equation (4) suggests two plausible measures of the profitability advantage of large firms that correspond at least broadly to δ_i in equation (1). The first is the elasticity of r_{cf} with respect to S_{cf}, evaluated at some central point (S^*,Π^*) in the observed size/profit distribution:

$$\left.\frac{Er_{cf}}{ES_{cf}}\right|_{S=S^*,\ \Pi=\Pi^*} = \left.\frac{dr_{cf}}{dS_{cf}}\right|_{S=S^*} \frac{S^*}{r^*} = -\frac{\alpha}{\Pi^*}, \tag{5}$$

where $r^* = \Pi^*/S^*$. The second is the relative difference between r^* and the asymptotic rate of return, β, which (4) predicts will be earned by very large firms:

$$\frac{\beta - r^*}{r^*} = \frac{\beta S^* - \Pi^*}{\Pi^*} \tag{6}$$

If $\Pi^* = \alpha + \beta S^*$, these two measures are equal.

Let $\hat{\alpha}$ and $\hat{\beta}$ be estimates of α and β, respectively. If these are obtained by applying least squares to (3) using firm-level data, measures (5) and (6) are automatically equal if S^* and Π^* are taken to be the corresponding sample means. But no such automatic relation holds for the estimation method used here (which is discussed in the next paragraph). Our measure of large-firm advantage, ϕ, is computed, following (5) and (6), by setting S^* equal to the sample mean firm size, $\overline{S}$, and Π^* equal to the corresponding predicted value from (3):[5]

$$\phi = - \hat{\alpha}/[\hat{\alpha} + \hat{\beta}\overline{S}] \tag{7}$$

Standard errors of these estimates are computed using the usual Taylor series approximation.

Summation of (3) over all firms in each size-class yields an equation that can be estimated using the data available:

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[5] Over the sample period, mean assets per firm grew at 5.8% per year, and mean business receipts grew at 4.6%. Using the implicit price deflator for nonresidential fixed investment, the real growth in mean assets per firm was about 1.2% per year. The real growth rate in mean business receipts was 1.1% using the implicit price deflator for GNP originating in manufacturing and roughly zero using the implicit price deflator for all GNP.

$$\Pi_c = \alpha N_c + \beta S_c + \epsilon_c, \qquad \text{where } \epsilon_c = \sum_{f=1}^{N_c} \epsilon_{cf}, \tag{8}$$

and Π_c, N_c, and S_c are total size-class profits, number of firms, and size (assets or business receipts), respectively. Since the last two variables differ considerably among size-classes in these data, least-squares estimation of (8) would be highly inefficient because of extreme heteroskedasticity. In Schmalensee (1987) I argued that it is plausible to assume that the standard deviation of ϵ_{cf} is proportional to $(A_{cf})^{\gamma}$, where A is total assets, and γ is a constant between 0.5 and 1.0. Under this assumption, the expected variance of ϵ_c is $N_c E[A^{2\gamma}|A \text{ in class } c]$. Making essentially the same the intra-class distributional assumptions as in Schmalensee (1987), these conditional expectations were estimated assuming $\gamma = 0.75$.[6] Weighted least squares was then employed to estimate (8).[7]

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[6]One change was made. Instead of the triangular distribution assumed for the largest size class in Schmalensee (1987), an exponential distribution, which places no artificial bound on the largest firm's size, was used here. (Eight-point Gaussian-Laguerre quadrature was employed for the numerical integration this procedure entailed.)

[7]Estimates of ϕ were also computed using the bounding values $\gamma = 0.50$ and $\gamma = 1.00$. Comparisons among these estimates (given in subsequent footnotes) test sensitivity to the relative weights assigned to large and small firms. To see this, note that for the asset-based profitability measures one can divide (8) by total class assets and describe the estimation method used by a set of weights that sum to one applied to this transformed equation. On average, the weights applied to firms with less than $1 million in total assets summed to 0.186 for $\gamma = 0.50$, 0.468 for $\gamma = 0.75$, and 0.730 for $\gamma = 1.00$. (These small firms accounted for 87.6% of total firms and 6.5% of total manufacturing assets on average.) Similarly, the weights applied to firms with more than $100

Inter-Industry Effects As noted above, I estimated (8) using data for all manufacturing corporations that is adjusted for inter-industry differences. I chose to use data on 2-digit industries for these adjustments, even though the IRS publishes data for more narrowly defined "minor industries". I thus attempt to estimate average changes in intra-industry size-profitability relations within two-digit industries, some of which may reflect inter-industry changes among more narrowly-defined industries.

There were four main reasons for the decision to work at the 2-digit level. First, missing size-class data and aggregated size classes pose additional estimation problems in this context (see footnote 9 below), and these problems are much more severe below the two-digit level. Second, these data are at the firm level and, as diversification proceeded throughout the sample period (see, e.g., MacDonald (1985)), it became less and less meaningful to assign firms to 3- or 4-digit industries. Third, working at the minor industry level would have roughly tripled the size of the data set. Since the data were assembled manually in order to obtain coverage of early years, this would have greatly increased the cost of this exploratory study. Finally, and most importantly, it did not appear that the benefits of disaggregation would be dramatic. Based on my earlier (Schmalensee 1987) results, the existence of substantial changes in the size-profitability relation within minor industries at least between 1963 and 1972 seemed clear. And there is substantial

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million summed to 0.405 for γ = 0.50, 0.136 for γ = 0.75, and 0.028 for γ = 1.00. (These large firms accounted for 0.3% of total firms and 68.6% of total manufacturing assets on average.)

homogeneity of intertemporal changes in many data sets within 2-digit industries.[8]

For each year, for all 12 measures of profitability, three different ϕ's were computed as follows. The first measure, ϕ^o, where "o" is short for "original," was constructed by estimating (3) and computing (8) using data for all manufacturing corporations. In principle these statistics reflect both average intra-industry advantages of size, in which we are interested, and inter-industry profitability differences that are correlated with inter-industry differences in firm size.

The second measure, ϕ^s, where "s" is short for "synthetic," was designed to reveal these inter-industry differences. For each year, six synthetic size-class profit totals were computed on the assumption that rates of return

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[8]Consider, for instance, studies of stock price changes by King (1966), Farrell (1974), and Livingston (1977), which indicate that industry disaggregation below (or even to) the 2-digit level adds essentially no explanatory power.

on assets were the same for all firms in each 2-digit industry.[9] Then equations (3) and (8) were applied to these data.

The third measure, ϕ^a, where "a" is short for "adjusted," was computed similarly using adjusted size class profit data, equal to [actual profits - synthetic profit + (mean return on assets)(total size class assets)]. By construction, total adjusted profits equals total actual profits; the adjustment removes the inter-industry differences captured by the synthetic series.

The ϕ^a are the theoretically preferred measures. But if the ϕ^s do not show significant variation over time, the ϕ^o are equivalent. In all that

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[9]Even at the 2-digit level, data for individual size classes were frequently unavailable, most often because size classes were combined. To produce estimates of each industry's assets in each size class in each year, I estimated the parameters of lognormal distributions for firms' assets for each 2-digit industry for each year, using data on the number of firms and total assets in the largest size classes. The estimates of the standard deviation of the log of assets in each industry were then smoothed over time to reflect the slow evolution of firm size distributions, using regressions involving time, time squared, and the fraction of firms in the industry employed in each year's estimation. The annual estimates of the means of the log of assets were then adjusted so that predicted and actual mean assets were equal for each industry for each year. For each year, the estimated lognormal distributions were used to produce estimates of the fractions of total manufacturing assets in each size class contributed by each 2-digit industry. These fractions were used to produce a size-class-specific weighted average of the industry rates of return on assets (r_1 -- r_6), which was in turn multiplied by total size-class assets to obtain the corresponding synthetic profit value (Π_1 -- Π_6). These were re-scaled where necessary so that total synthetic profits equalled total actual profits. (This last step involved changes of 1% or less in all cases.)

follows subscripts on the ϕ's indicate the measure of profitability employed. Thus, for instance, ϕ_5^a uses the adjusted profit figures corresponding to r_5.

3. Annual Estimation Results

We must first see if the estimated ϕ's contain any information at all. Do these statistics indicate that the true intra-industry relations change over time? Do they indicate that the pattern of changes depends on the profitability measure used?

Averages and Changes One can consider the 31 true values of any particular ϕ to be draws from some distribution with mean μ and variance σ^2. The estimated ϕ's are then equal to these true values plus sampling errors, which have zero means and variances equal to the squared standard errors of estimate. Following Schmalensee (1987, p. 412), for instance, one can summarize the estimated ϕ's by estimating μ and σ and performing large-sample χ^2 tests of various hypotheses of interest.[10] Table 3 and the paragraphs that follow present the results of these computations.

For all 24 ϕ^o and ϕ^a measures, χ^2 tests reject the null hypothesis that all annual values are zero at well below the 1% level. (The test statistics are distributed as χ^2 statistics with 31 degrees of freedom under the null hypothesis; all exceed 1000.) All the estimated means of the ϕ^o and ϕ^a distributions are positive, and all are at least 7 times their large-sample standard errors, indicating that large firms are generally more profitable than

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[10] These tests treat the estimation errors in the ϕ's as serially independent, though one might well expect some positive correlation. The results presented below are so strong, however, that it seems unlikely that they merely reflect plausible departures from independence.

small firms. Indeed, *all* of the 744 estimates of ϕ^o and ϕ^a are positive,[11] and the 24 means of the annual t-statistics all exceed 5.5. The observed profitability advantage of large firms may, of course, reflect only systematic size-related differences in accounting practices (see, for instance, Salamon (1985)), but it is a strong feature of this data set.[12]

For 10 of the 12 profitability measures, the null hypothesis that all the ϕ^s are zero can be rejected at the 10% level. As Table 3 shows, the estimated means of the ϕ^s distributions are tiny relative to the corresponding means of the ϕ^o and ϕ^a for the asset-based profitability measures, but substantial for the six sales-based measures. Thus, while the ϕ^o for the sales-based profitability measures are well above those for the corresponding asset-based measures, the six corresponding ϕ^a pairs are roughly equal. These results imply that inter-industry differences in rates of return on assets are generally unrelated to differences in average firm size, while large manufacturing firms have higher rates of return on sales than small firms on average in large part because they tend to be in industries with higher capital/output ratios.

The estimated μ's shown in Table 3 indicate that the accounting profitability advantage of firms above the mean size is on average small. Using equation (6), for instance, if the mean rate of return were 10.0%, the

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[11]All but 8 of the estimates of ϕ^o and ϕ^a computed with $\gamma = 0.5$ were positive, as were all but 2 of the estimates computed with $\gamma = 1.0$.

[12]It is worth noting, however, a positive intra-industry correlation between firm size and profitability is *not* a strong feature of data on IRS minor industries; see Caves and Pugel (1980) and Schmalensee (1987, forthcoming). This suggests that even the ϕ^a reflect some inter-industry effects.

expected rate of return of the largest manufacturing firms would be between 10.069% and 10.469% using the means of the ϕ^o distributions and between 10.066% and 10.242% using the means of the ϕ^a distributions. It is thus not surprising that many studies that use data on only very large firms fail to find a systematic relation between size and accounting profitability.

Generally, the ϕ^o and ϕ^a based on after-tax profits are larger than those based on before-tax profits. To see why, let Π be net profits of firms in some size class, L be total losses (expressed as a positive number) of firms in that class that incur losses, and τ be the corporate tax rate applied to firms with positive profits. Then the ratio of taxes to size-class net profit is equal to $\tau[1 + (L/\Pi)]$. Because the variance of profit rates declines with firm size, the ratio (L/Π) is higher for the smaller size classes. Thus the ratio of taxes to net income is generally higher for small firms than for large firms. It is less clear why more inclusive profit measures generally produce smaller estimated ϕ's.

Let us now consider variation in the ϕ's over time. For all 24 ϕ^o and ϕ^a measures, χ^2 tests overwhelmingly reject the null hypotheses of constancy over time. (The test statistics are distributed as χ^2 with 30 degrees of freedom under the null hypotheses; all exceed 140.) That is, not only are these estimates relatively precise in most years, as the mean t-statistics indicate, but the estimated ϕ's vary much more over time than is consistent with sampling variation alone. There is a signal here, not just noise.

On the other hand, for all but one of the ϕ^s distributions, the null hypothesis of no change is *not* rejected at even the 10% level. There is essentially no evidence that the intertemporal variation in the ϕ^o reflects variation in inter-industry profitability relations.

The ϕ^o and ϕ^a series based on after-tax profits are generally more variable than the corresponding before-tax series, presumably because the loss/profit ratio (L/Π in the discussion above) varies most over time for small size classes. And, among after-tax or before-tax series, estimated coefficients of variation tend to be higher for ϕ's based on more inclusive profit measures.

Parallel Movements The fact that the underlying ϕ parameters appear to vary over time does not, of course, establish that there is *systematic* variation. One piece of reassurance on this score is provided by a comparison of estimates for 1963 and 1972, the two years between which Schmalensee (1987) detected a sharp decline in the profitability advantage of firms with large market shares (as measured by δ_i in (1)) within IRS minor industries. Consistent with those disaggregate results, all 24 of the estimated ϕ^o and ϕ^a measures decline substantially between these two years. The inter-quartile range of the percentage declines is [32%, 44%] for the 12 ϕ^o series and [31%, 46%] for the 12 ϕ^a's.

More generally, all these estimates move together over time. Table 4 presents correlations among the estimated ϕ^o, among the estimated ϕ^a, and between the ϕ^o and ϕ^a that use the same profitability measure. The correlations among the ϕ^o and among the ϕ^a are generally very high.[13] The 12 correlations between the asset-based ϕ's and the sales-based ϕ's using the

[13]Correlations among the ϕ^o and ϕ^a based on γ=0.75 and the corresponding estimates based on γ=0.50 and γ=1.0 were also generally high. The lowest of the 24 correlations between the γ=0.75 and γ=0.50 estimates was .89 (for ϕ_7^o); the second-lowest was 0.95. The correlations between the γ=0.75 and γ=1.0 estimates were relatively low for r_1 (0.41 for ϕ_1^o and -.11 for ϕ_1^a) and r_7 (-.26 for ϕ_7^o), but the lowest of the others was 0.89.

same profit measure are all at least 0.95. Similarly, the lowest of the 12 correlations between ϕ's based on before-tax profits and those based on the corresponding after-tax measure was 0.87. The fact that all these ϕ's tend to move together so closely over time suggests the existence of changes in intra-industry profitability relations that do not merely reflect accounting biases.

Note also that all the correlations between the ϕ^o and ϕ^a that use the same profitability measure are greater than 0.95. That is, even assuming the presence of non-constant size-related inter-industry differences, the measures of large firm advantage based on data for all manufacturing firms are almost perfectly correlated over time with the measures based on data adjusted for inter-industry differences.

In light of the high correlations between the ϕ^o and the ϕ^a, a case could be made for limiting attention to either set. The ϕ^a are better in principle, but the tests summarized in Table 3 suggest that adjustment used to compute them may only add noise. Since neither set is obviously superior, I report results for both in what follows.

4. Patterns of Change

Since it is not clear what significance, if any, to attach to differences in the means of the different ϕ's, all 24 sets of estimates were re-scaled so that each had a sample mean of unity, and the estimated standard errors were re-scaled accordingly. This facilitates comparison of estimated coefficients across ϕ's in the descriptive regressions reported below.

Overall Trends The most obvious feature revealed by plots of all 24 of these series is a strong downward trend for most of the sample period. All 24

ϕ^a and ϕ^o series attained their minimum value in 1978 or 1979, for instance.[14] Estimates of the overall trends are presented in Table 5. The variable T is equal to the year of the observation minus 1952. The coefficient estimates and standard errors were computed using weighted least squares, allowing for both sampling error and a homoscedastic additive disturbance.[15] The estimated coefficients were multiplied by 100 so that the figures shown in Table 5 are the estimated average annual change in each ϕ as a percentage of the sample mean of the corresponding estimates.

All the trend coefficients are highly significant: all 24 t-statistics exceed 3.0 in absolute value, and all but 2 (for ϕ_1^a and ϕ_7^a) exceed 4.0. And the estimated rates of decline are substantial: all ϕ's are estimated to decline by at least 2% per year on average, and 18 out of 24 estimates exceed 3% per year.

I know of no persuasive explanation for the prolonged decline in the profitability advantage of large firms detected here.[16] *A priori*, this trend may merely reflect changes in size-related differences in accounting

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[14]This was also true for the all the estimates computed with γ=0.5, for all but one of the ϕ^o series computed with γ=1.0, and for 8 out of the 12 ϕ^a series computed with γ=1.0.

[15]The two-step estimation procedure described in Schmalensee (1987, Appendix B) was employed. The natural degrees-of-freedom adjustment was made because of the smaller sample sizes here, and negative estimated disturbance variances were set to zero.

[16]Some insight may be provided by re-writing (7) as $\phi = 1/[(\bar{S})(-\hat{\beta}/\hat{\alpha}) - 1]$. For all 24 ϕ^o and ϕ^a series, $(-\hat{\beta}/\hat{\alpha})$ either declined over time or rose less rapidly than $(\bar{S})$. It is not clear how to interpret this, however, since it is not clear that there is anything artificial about the secular increase in the mean size of manufacturing firms.

practices. But it is not at all clear exactly what plausible changes of this sort would produce such strong declines in all these measures. Size-related differences in the adoption of accelerated depreciation for tax purposes, for instance, should have no effect on ϕ's based on r_{11} and r_{12}, but these show among the strongest trends. The results shown in Table 5, along with those reported below, at least suggest a secular change -- of unknown origin -- in the relations between the economic profitability of large and small firms in U.S. manufacturing industries. Moreover, as the results reported below indicate, this change cannot be simply explained as a consequence of the sharp increase in energy prices and foreign competition in the 1970's.

The R^2 and SER (standard error of regression) statistics in Table 5 were computed by regressing the actual ϕ's on the predicted values from weighted least squares. The R^2's are generally higher for before-tax than after-tax profitability measures and, within these categories, the more inclusive the profit measure used. The SER's here and the estimated coefficients of variation in Table 3 show that the after-tax measures vary more around their trends as well as around their means than the before-tax measures. But within these categories, the ϕ's based on more inclusive measures of profit, which Table 3 showed to have higher coefficients of variation, generally have more important trend components and *less* variation around their trends.

Cyclical Variation The results reported so far in this section may suggest that the high correlations shown in Table 4 simply reflect the presence of strong, common trends. Table 6 refutes this suggestion by presenting correlations among de-trended ϕ's. (Ordinary least squares was employed here to ensure orthogonality of trends and de-trended series.) All correlations are positive. And, though they are on average somewhat smaller

than the corresponding statistics in Table 4, they are still generally quite high. All but two of the diagonal elements of this matrix exceed 0.95, for instance, and 36 of 132 off-diagonal elements are greater than or equal to 0.90 (as compared to 71 in Table 4). We now turn to a descriptive analysis of the these apparently coordinated deviations from trend.[17]

The following three sets of aggregate cyclical variables were employed in exploratory regressions:

1. Indicators of the *level of real activity* relative to capacity: the unemployment rate (U) and capacity utilization in manufacturing (CU), both expressed as percentages.
2. Indicators of the *rate of change of real activity*: the percentage changes in manufacturing sales (DSA) and in real GNP originating in manufacturing (DRGNP).
3. Indicators of the *rate of inflation*: the percentage changes in the implicit price deflator for gross national product originating in manufacturing (DPGNP), the Wholesale Price Index

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[17]Since (7) implies $\phi = 1/[(\bar{S})(-\hat{\beta}/\hat{\alpha}) - 1]$, one might worry that parallel movements in the estimated ϕ's simply reflects pro-cyclical deviations of both mean assets and business receipts from their trends. Since ϕ is a function only of $(\bar{S})(-\hat{\beta}/\hat{\alpha})$, one can use the identity $\Delta(XY) = \Delta X(\bar{Y})+\Delta Y(\bar{X})$ to allocate year-to-year changes in ϕ between changes in $\bar{S}$ and changes in $(-\hat{\beta}/\hat{\alpha})$. One can then decompose the variance of changes in ϕ, a measure of the importance of deviations of ϕ from its trend, into components reflecting the variance of changes in $\bar{S}$, the variance of changes in $(-\hat{\beta}/\hat{\alpha})$, and the covariance between these changes. For all 24 ϕ^o and ϕ^a series, the first of these components accounted for no more than 20% of the variance of changes in ϕ, and the second component accounted for no less than 68%.

for crude materials for further processing (DPCM), and gross average hourly earnings in manufacturing (DW).

All these variables were taken from the 1987 *Economic Report of the President.* In addition, detrended average manufacturing profitability ($\tilde{r}_1$ -- $\tilde{r}_{12}$) was employed as an independent variable. Generally the correlations between $\tilde{r}$ and CU and between $\tilde{r}$ and DSA were nearly equal. The deviation of average profitability from trend thus reflects both the level of real activity relative to capacity and the rate of change of real activity. Since there are only 31 years in the sample period, correlations between a number of these variables are high, and theory does not much help restrict specifications, considerations of robustness led to concentration on results that seemed broadly consistent across all 24 ϕ's analyzed.

When variables in both the first and second sets were employed in exploratory regressions, the latter were never significant. Thus changes in ϕ seem more closely related to the level of economic activity relative to capacity than to changes in output or sales: the relevant contrast seems to be between cyclical peaks and troughs, rather than between periods of expansion and contraction. The correlation between U and CU is -0.88, and both performed well in exploratory regressions when the other was excluded. But U has a much stronger trend component than CU (correlations with T are 0.65 and -0.40, respectively). Since most observers agree that the secular increase in the U.S. unemployment rate over this period reflects structural changes in labor markets rather than a trend toward increasing slack in those markets, I chose to work with CU instead of U. In the third set of variables, DW consistently outperformed the other two.

Weighted least squares estimates of linear specifications involving cyclical variables and trends are presented in Table 7. Note first that all but 3 of the 96 estimated coefficients are negative, and all of the significant coefficients are negative. The R^2's are all between 0.79 and 0.97. Once again all 24 series exhibit similar behavior. The narrower range of R^2's, as compared to Table 5, indicates that in general cyclical variables contribute more to the explanation of those ϕ's with less pronounced trends.

Except for the equations involving ϕ_5^a, ϕ_{12}^o, and ϕ_{12}^a, either $\tilde{r}$ or CU, or both, have a negative coefficient significant at the 5% level. And in those cases both coefficients are negative and jointly significant at the 1% level. The profitability advantages of large firms is thus generally higher at cyclical troughs, when both $\tilde{r}$ and CU are low, than at peaks.

This is a somewhat surprising finding. Since large firms are more likely to be unionized than their smaller rivals, for instance, one might expect larger firms to face less strongly pro-cyclical labor costs. And, since large firms tend to have higher capital/output ratios than their smaller rivals (Caves and Pugel (1980)), one might expect them to have higher ratios of fixed to variable cost and thus to show wider profit fluctuations for comparable output variations. But either of these differences would produce pro-cyclical movement in the ϕ's. The observed counter-cyclical movement is thus strongly consistent with the finding of Mills and Schumann (1985) that larger firms experience smaller relative variations in output: they contract less in recession and expand less in prosperity than their smaller rivals.[18]

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[18]Mills and Schumann (1985) provide a theoretical rationale for this pattern. Also relevant here is the Rotemberg-Saloner (1986) argument that collusion is likely to be more effective at troughs than at peaks. But if one

Even though the correlation between T and DW is 0.71, all but one of the trend coefficients (the one for ϕ^a_{11}) are highly significant. And in that case both coefficients are negative and jointly significant at the 0.5% level. The addition of cyclical variables does not erase the picture drawn by Table 7: the profitability advantage of large firms in U.S. manufacturing has apparently declined steadily and substantially over time.

To see if the secular decline in the ϕ's could be a symptom of the increases in energy prices and foreign competition that marked the 1970's, I allowed the trend coefficient in these equations to shift between 1968 and 1969, in the middle of the sample. Sixteen of the 24 weighted least squares equations implied a *fall* in the rate of decline in the later years; 6 of these differences were significant at the 5% level. Only one of the eight differences implying an increase in the rate of decline (that for ϕ^o_{12}) was significant at this level. The sign pattern of the other coefficients was unaffected by the addition of a second trend variable, and all the estimated changes in the trend coefficient were less than 0.50 in absolute value. It thus seems quite clear that whatever drove the secular decline in the ϕ's

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thinks of their model as applying to concentrated industries in which a few leading firms face a competitive fringe, the fringe will generally benefit relatively more from collusion than the colluding leaders, and pro-cyclical movement in the ϕ's should result. Given the mix of concentrated and unconcentrated industries in our sample, however, the counter-cyclical movements observed here hardly cast much doubt on the Rotemberg-Saloner theory. (See Domowitz, Hubbard, and Petersen (1987) for generally supportive tests of this theory.)

operated at least as strongly in the first half of the sample period as in the more turbulent second half.[19]

The weakest of the variables used in these regressions is DW. All but two of the estimated coefficients of this variable are negative, however, and over half are significant at the 5% level. There is thus some evidence here that the profitability advantage of large firms tends to erode when inflation -- particularly wage inflation -- is high.

Comparisons with DHP Estimates Let us now relate these findings to the inter-industry results obtained by DHP (1986, Table 2). They present annual estimates of the following regression for the period 1958-81:

$$PCM = \theta_o + \theta_{cr}(CR_4) + \theta_{kq}(K/Q) \tag{9}$$

In this equation PCM is the Census price-cost margin, equal to the value of output (sales plus inventory change) minus the cost of labor and materials, divided by the value of output. As was noted above, the closest of our profitability measures is r_{12}. The independent variables are the four-firm concentration ratio, CR_4, and the capital/output ratio, K/Q. As is discussed in Schmalensee (forthcoming), the parameter θ_{kq} is most plausibly interpreted

[19]Because all 24 series attained their minimum values in 1978 or 1979, there is some suggestion of a change in these trends near the end of the sample period. But coefficients of T^2 and a variable allowing the trend to shift between 1978 and 1979 were generally insignificant when added to the equations shown in Table 7. It thus seems likely that the apparent post-1978 shifts in these trends reflect instead responses to the sharp cyclical changes that occurred during the 1979-83 period. (The unemployment rate rose from 5.8% in 1979 to 9.5% in 1982 and 1983.) Data on later years will be required to distinguish definitively between these possibilities, of course.

as the average competitive rate of return on capital plus the average annual depreciation rate.

The standard errors of $\hat{\theta}_{cr}$ and $\hat{\theta}_{kq}$, the estimates of θ_{cr} and θ_{kq}, reported by DHP change relatively little over the 1958-81 period, but both coefficients decline substantially. The R^2 of equation (9) drops from an average of 0.176 in the first five years of this period to an average of 0.026 in the last five years. All three parameters decline substantially between 1963 and 1972, the two years studied by Schmalensee (1987) -- consistent with both the weakening in the correlation between the ρ_i and concentration and the general decline in the δ_i reported there.

Using panel data, DHP report that θ_{cr} and θ_{kq} are more sensitive to U than to the percentage change in industry sales. They interpret this to mean that economy-wide labor market developments are more important than industry-specific demand changes. Regression analysis of their annual estimates using the cyclical variable introduced above yields similar results. As above, variables in the second (rate of change) set never contribute significantly to explaining variation in $\hat{\theta}_{cr}$, $\hat{\theta}_{kq}$, or R^2 when variables in the first (level) set are employed. But, since DSA and DRGNP are economy-wide measures here, it seems at least as reasonable to interpret the DHP results as indicating that the parameters of (9), like the ϕ's, respond more to differences between peaks and troughs rather than to differences between expansions and contractions.

As above, U and CU performed similarly in regressions involving the DHP parameters, and CU was selected for further analysis because it does not contain such a strong trend. The most natural profitability variable, $\tilde{r}_{12}$, generally had an insignificant coefficient. Among the inflation variables, output price changes (DPGNP) consistently outperformed wage changes (DW).

Table 9 presents regressions of the annual DHP estimates, re-scaled to have sample means of unity to facilitate comparisons, on the variables that performed best in exploratory regressions. Because the standard errors of the b's varied little over time, ordinary least squares was employed.

Note first that, like the ϕ's, all three DHP parameter estimates show significant downward trends. DHP do not report estimates involving trends, but they employ U, which has a strong trend, rather than CU, which does not. Since they find that $\hat{\theta}_{cr}$ is negatively related to U, and U tends upward over the sample period, their estimated coefficient of U seems to reflect a declining trend as well as pro-cyclical variations around trend.

Inspection of a plot of $\hat{\theta}_{cr}$ reveals that, unlike the ϕ's and the other DHP statistics analyzed here, it does not decrease smoothly over this period. The variable DCR, equal to zero until 1971, 0.33 in 1972, 0.67 in 1973, and one in 1974 and later years, explains 93% of the variation in $\hat{\theta}_{cr}$ by itself, and it consistently outperforms T, as the second equation in Table 8 indicates. It is not clear what permanent structural change in the U.S. economy occurred between 1971 and 1974 that might account for this pattern. (Most of the drop in $\hat{\theta}_{cr}$ occurred prior to the first oil shock in late 1973, and no effect of the second oil shock is visible in this series.)[20]

The coefficients of CU are positive in all the regressions in Table 9. Thus using a different cyclical variable and allowing for both trends and

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[20]As above, I added a post-1968 trend variable these equations to test for acceleration or deceleration over time. This variable was insignificant when added to the second and third equations reported in Table 8. The modified fourth equation showed a statistically significant increase in the rate of decline of R^2, but the estimated increase was only 0.38 percentage points per year.

inflation, we nevertheless confirm the DHP finding that the inter-industry relation between concentration and average profitability (as measured by the PCM) is stronger at cyclical peaks than at troughs.

If inter-industry profitability differences merely reflected intra-industry differences (large δ_i on average in (2)), as Demsetz (1973, 1974) has argued, this finding should be reversed, since the intra-industry relation between size and profitability (as measured here by ϕ) is weakest at peaks. The obvious inference is that difference between the *industry-level* cyclical effects (related to the ρ_i in equation (2)) affecting concentrated and unconcentrated industries is even stronger than DHP's estimates suggest. In terms of equation (2), the correlation between the ρ_i and concentration must generally increase by more than enough at cyclical peaks to outweigh the apparent contemporaneous decline in the average δ_i.

Finally, the estimated effects of inflation on the DHP parameters are mixed. The coefficient of concentration falls when inflation is high, parallelling the apparent behavior of the ϕ series. But $\hat{\theta}_{kq}$ and the R^2 of (9) apparently tend to rise when inflation is high, all else equal. I have no plausible interpretation of this pattern to offer.

5. Conclusions and Implications

Three results of this study seem particularly noteworthy. *First, 12 measures of ϕ, the profitability advantage of large U.S. manufacturing firms over their smaller rivals, changed significantly and in parallel over time*, despite substantial differences in the movements of the underlying profitability measures, whether or not allowance was made for size-related inter-industry differences. These coordinated changes seem difficult to

explain away by accounting biases; it seems more likely that they reflect (though perhaps imprecisely) changes in relations involving economic profitability.

Second, all measures of ϕ declined significantly and substantially during the period 1953-83, with no visible acceleration during the turbulent second half of this period. This decline can be roughly interpreted as a general fall in the δ_i in equations (1) and (2), which, in turn, could "explain" (in a mechanical sense) the contemporaneous secular decline in the strength of the inter-industry relation between concentration and average profitability reported by DHP. But the two trends are not exactly parallel, and their causes are by no means certain.

Third, all measures of ϕ varied counter-cyclically around their trends during the sample period. This suggests general counter-cyclical movement in the δ_i in equation (1). But equation (2) makes clear that such movement would by itself imply counter-cyclical variation in the strength of the concentration-profitability correlation, not the pro-cyclical variation reported by DHP.[21]

The most natural reconciliation of these findings is that pro-cyclical variation in the correlation between the ρ_i and concentration, which would be produced by pro-cyclical variation in the incidence of collusion in concentrated industries, is strong enough to offset counter-cyclical movement of the δ_i. Pro-cyclical movements in the concentration-profitability relation thus appear likely to reflect industry-level effects that are masked, not exaggerated, by changes in intra-industry relations. These findings, taken

[21]A comparison of Tables 7 and 8 also suggests the possibility of qualitatively different intra- and inter-industry responses to inflation.

together, thus seem to weigh against the Demsetz (1973, 1974) view that apparent inter-industry differences generally reflect only intra-industry heterogeneity.[22] But, again, the underlying causes of these patterns are unclear.

Two directions for future research are suggested by these findings. First, there is a clear need for theoretical work on dynamic market models that can capture both inter-industry and intra-industry differences, particularly in response to cyclical demand shifts. The studies of Mills and Schumann (1985) and Rotemberg and Saloner (1986) are important first steps, but there is plainly more to be done.

Second, this exploratory study used all-manufacturing averages adjusted for industry effects at the two-digit level. In light of the systematic patterns observed here, it seems worthwhile to investigate intertemporal changes in ϕ or related measures at lower levels of aggregation. Such work would provide a check on the validity of the results of this study (see footnote 12, above) and might well reveal informative inter-industry differences in the patterns of changes in ϕ over time.[23]

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[22]For more on this issue, see Mueller (1986) and Schmalensee (1985, 1987).

[23]Schmalensee (1987) found a variety of differences between 1963 -- 1972 changes in durable and nondurable goods industries, for instance.

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Table 1

Measures of Profitability Employed

Profit Measures:

Π_1 = After-Tax Profit

Π_2 = Before-Tax Profit

Π_3 = After-Tax Profit + Interest Payments

Π_4 = Before-Tax Profit + Interest Payments

Π_5 = After-Tax Profit + Interest Payments + Depreciation

Π_6 = Before-Tax Profit + Interest Payments + Depreciation

Size Measures:

A = Total Assets

R = Business Receipts

Profitability Measures:

Measure	Mean (%)[a]	Trend (%)[b]	$\sigma(r)/\mu$[c]	$\sigma(\epsilon)/\mu$[d]
$r_1 = \Pi_1/A$	4.29	-17.3 (4.3)	.261	.212
$r_2 = \Pi_2/A$	8.44	-19.8 (3.5)	.249	.174
$r_3 = \Pi_3/A$	5.94	4.7 (2.7)	.141	.136
$r_4 = \Pi_4/A$	10.09	-6.5 (2.8)	.147	.137
$r_5 = \Pi_5/A$	9.66	5.3 (1.6)	.090	.077
$r_6 = \Pi_6/A$	13.82	-3.1 (1.8)	.094	.092
$r_7 = \Pi_1/R$	3.20	-12.6 (3.8)	.215	.186
$r_8 = \Pi_2/R$	6.30	-14.5 (2.8)	.191	.140
$r_9 = \Pi_3/R$	4.50	10.3 (1.8)	.130	.092
$r_{10} = \Pi_4/R$	7.60	-0.8 (1.9)	.092	.094
$r_{11} = \Pi_5/R$	7.34	10.9 (2.0)	.115	.059
$r_{12} = \Pi_6/R$	10.44	2.7 (1.2)	.064	.061

[a]Sample mean (1953-1983) of all-manufacturing average.

[b]Trend coefficient from ordinary least squares regression, as a percentage of the sample mean; standard error in parentheses.

[c]Coefficient of variation of all-manufacturing average.

[d]Standard error of trend regression divided by sample mean.

Table 2

Correlations among Measures of Manufacturing Profitability

Levels

Detrended	1	2	3	4	5	6	7	8	9	10	11	12
1	-	.97	.53	.91	.29	.90	.97	.97	.06	.76	-.38	.27
2	.97	-	.40	.91	.11	.86	.91	.98	-.11	.70	-.53	.15
3	.94	.95	-	.73	.89	.78	.53	.39	.83	.84	.40	.65
4	.92	.98	.97	-	.44	.97	.85	.86	.27	.88	-.25	.37
5	.91	.86	.90	.84	-	.59	.35	.15	.91	.67	.71	.79
6	.94	.97	.96	.97	.94	-	.86	.84	.38	.91	-.07	.52
7	.97	.91	.85	.82	.88	.87	-	.96	.14	.78	-.24	.40
8	.96	.95	.87	.89	.85	.92	.97	-	-.05	.73	-.43	.27
9	.88	.87	.92	.88	.89	.90	.87	.88	-	.61	.83	.80
10	.90	.93	.90	.93	.84	.93	.87	.95	.96	-	.18	.75
11	.36	.27	.27	.21	.56	.39	.49	.46	.58	.49	-	.73
12	.68	.67	.60	.61	.75	.73	.75	.80	.82	.84	.86	-

Note: Numbers above the diagonal are correlations among the all-manufacturing averages of the indicated profitability measures. Numbers below the diagonal are correlations among residuals from least squares regressions of these measures on a linear trend.

Table 3

Distributions of Annual Estimates of ϕ

Profitability Measure (m)	ϕ_m^o $\hat{\mu}$	ϕ_m^o $\lvert\hat{\sigma}/\hat{\mu}\rvert$	ϕ_m^s $\hat{\mu}$	ϕ_m^s $\lvert\hat{\sigma}/\hat{\mu}\rvert$	ϕ_m^a $\hat{\mu}$	ϕ_m^a $\lvert\hat{\sigma}/\hat{\mu}\rvert$
1	.0246	.473	-.0001	5.2	.0242	.471
2	.0157	.372	-.0002	0[a]	.0158	.339
3	.0170	.575	-.0001	0[a]	.0168	.536
4	.0127	.463	-.0001	0[a]	.0128	.420
5	.0070	.762	0[b]	0[a]	.0067	.703
6	.0069	.610	0[b]	0[a]	.0068	.541
7	.0469	.407	.0079	0[a]	.0237	.418
8	.0324	.276	.0079	0[a]	.0147	.298
9	.0347	.437	.0081	0[a]	.0164	.506
10	.0275	.327	.0081	0[a]	.0119	.383
11	.0192	.420	.0081	0[a]	.0070	.637
12	.0185	.334	.0081	0[a]	.0066	.486

[a] A χ^2 test does not reject at the 10% level the hypothesis that the ϕ's are equal in all years.

[b] A χ^2 test does not reject at the 10% level the hypothesis that the ϕ's are zero in all years.

Table 4

Correlations among Estimated ϕ Series

	Original 1	2	3	4	5	6	7	8	9	10	11	12
Adjusted 1	.96	.92	.81	.79	.69	.68	.98	.91	.82	.77	.71	.67
2	.88	.97	.95	.95	.85	.86	.85	.97	.96	.94	.90	.89
3	.66	.90	.99	.99	.95	.96	.69	.88	.98	.94	.97	.94
4	.63	.91	.99	.99	.93	.96	.67	.90	.99	.97	.98	.97
5	.51	.74	.93	.90	.99	.99	.54	.73	.90	.84	.96	.91
6	.50	.78	.95	.94	.98	.99	.53	.77	.92	.89	.99	.95
7	.99	.93	.75	.73	.61	.60	.99	.87	.72	.69	.59	.57
8	.84	.99	.89	.91	.73	.77	.91	.98	.93	.94	.84	.86
9	.62	.87	.99	.98	.94	.96	.72	.87	.99	.98	.96	.95
10	.59	.89	.98	.99	.89	.95	.70	.90	.98	.99	.95	.97
11	.48	.72	.92	.88	.99	.98	.58	.71	.94	.88	.96	.99
12	.47	.75	.94	.93	.98	.99	.57	.76	.95	.94	.98	.96

Note: Numbers above the diagonal are correlations among the estimated ϕ^o for the indicated profitability measures. Diagonal entries are correlations between ϕ^o and the corresponding ϕ^a. Numbers below the diagonal are correlations among estimated ϕ^a.

Table 5

Trend Analysis of Estimated ϕ Series

Profitability Measure (m)	Dependent Variable: ϕ_m^o 100xT (S. E.)	R^2	SER	Dependent Variable: ϕ_m^a 100xT (S. E.)	R^2	SER
1	-3.39 (0.74)	.285	.413	-2.93 (0.74)	.110	.478
2	-3.16 (0.53)	.564	.256	-2.65 (0.54)	.399	.276
3	-5.56 (0.54)	.795	.265	-5.16 (0.52)	.772	.261
4	-4.47 (0.42)	.812	.205	-4.06 (0.42)	.759	.213
5	-7.62 (0.61)	.843	.309	-7.22 (0.55)	.852	.279
6	-5.80 (0.39)	.882	.212	-5.46 (0.35)	.894	.180
7	-2.69 (0.65)	.156	.407	-2.33 (0.72)	.183	.386
8	-2.41 (0.46)	.448	.235	-2.23 (0.49)	.384	.248
9	-4.07 (0.44)	.751	.225	-4.98 (0.46)	.804	.228
10	-3.30 (0.35)	.721	.190	-3.76 (0.38)	.759	.195
11	-4.23 (0.29)	.877	.155	-6.59 (0.49)	.856	.249
12	-3.66 (0.27)	.844	.149	-4.91 (0.33)	.881	.171

<u>Note</u>: Trend coefficients and standard errors are from weighted least squares estimation. The R^2 and SER (standard error of regression) statistics are from a regressions of the estimated ϕ series on the weighted least squares predictions.

Table 6

Correlations among De-trended Estimates of ϕ's

Adjusted	Original 1	2	3	4	5	6	7	8	9	10	11	12
1	.98	.94	.88	.83	.61	.61	.98	.87	.84	.71	.72	.55
2	.91	.97	.93	.96	.60	.70	.91	.96	.94	.88	.85	.75
3	.81	.92	.98	.94	.74	.76	.81	.83	.94	.77	.84	.65
4	.74	.94	.94	.96	.62	.77	.79	.92	.96	.91	.90	.83
5	.57	.53	.67	.49	.99	.93	.50	.40	.51	.30	.74	.41
6	.59	.71	.78	.75	.88	.96	.52	.55	.62	.52	.88	.68
7	.99	.95	.87	.81	.61	.66	.99	.89	.83	.73	.68	.56
8	.86	.99	.92	.95	.53	.74	.91	.97	.94	.95	.81	.82
9	.76	.89	.99	.94	.68	.81	.83	.90	.97	.93	.85	.79
10	.66	.89	.90	.98	.46	.76	.74	.93	.91	.96	.82	.91
11	.49	.45	.61	.42	.99	.86	.54	.46	.63	.42	.71	.90
12	.48	.61	.70	.67	.86	.97	.55	.67	.73	.72	.86	.71

Note: Numbers above the diagonal are correlations among the residuals from regressions of the ϕ^o for the indicated profitability measures on trends. Diagonal entries are correlations between residuals for the ϕ^o and the corresponding ϕ^a. Numbers below the diagonal are correlations among similarly detrended ϕ^a.

Table 7

Weighted Least Squares Regressions Involving ϕ's

	Dependent Variable: ϕ^o_m					Dependent Variable: ϕ^a_m				
m	$\tilde{r}_m$	CU	100xT	DW	R^2	$\tilde{r}_m$	CU	100xT	DW	R^2
1	-.223	-.029	-3.11	-.037	.874	-.250	-.024	-2.33	-.043	.795
	(.043)	(.008)	(0.50)	(.018)		(.039)	(.007)	(0.47)	(.017)	
2	-.078	-.025	-2.99	-.030	.893	-.098	-.021	-2.24	-.040	.912
	(.020)	(.006)	(0.44)	(.015)		(.018)	(.005)	(0.48)	(.014)	
3	-.085	-.035	-6.02	-.016	.941	-.122	-.030	-5.48	-.019	.954
	(.047)	(.007)	(0.48)	(.018)		(.040)	(.006)	(0.40)	(.016)	
4	-.042	-.023	-4.61	-.017	.933	-.068	-.018	-4.08	-.018	.943
	(.021)	(.005)	(0.38)	(.013)		(.019)	(.005)	(0.32)	(.011)	
5	-.063	-.028	-8.62	.021	.886	-.090	-.024	-8.14	.019	.901
	(.086)	(.014)	(0.87)	(.031)		(.078)	(.012)	(0.77)	(.028)	
6	.005	-.025	-6.18	-.011	.904	-.021	-.019	-5.71	-.008	.930
	(.027)	(.007)	(0.48)	(.016)		(.025)	(.006)	(0.42)	(.015)	
7	-.425	-.008	-1.29	-.068	.880	-.434	-.013	-1.58	-.054	.924
	(.044)	(.004)	(0.39)	(.013)		(.049)	(.006)	(0.34)	(.011)	
8	-.192	-.006	-1.77	-.042	.888	-.197	-.009	-1.85	-.034	.898
	(.029)	(.005)	(0.32)	(.011)		(.034)	(.006)	(0.35)	(.011)	
9	-.286	-.011	-3.61	-.039	.957	-.273	-.020	-4.98	-.025	.963
	(.077)	(.005)	(0.34)	(.010)		(.073)	(.006)	(0.34)	(.012)	
10	-.187	-.002	-2.92	-.026	.917	-.177	-.007	-3.66	-.017	.938
	(.042)	(.005)	(0.28)	(.009)		(.042)	(.006)	(0.31)	(.010)	
11	-.078	-.013	-3.92	-.040	.922	-.352	-.009	-6.16	-.036	.909
	(.081)	(.005)	(0.40)	(.016)		(.157)	(.012)	(0.93)	(.036)	
12	-.065	-.007	-3.37	-.030	.889	-.115	-.008	-4.81	-.015	.925
	(.053)	(.005)	(0.36)	(.011)		(.064)	(.008)	(0.50)	(.016)	

Note: Figures in parentheses are standard errors. R^2 statistics are the squares of the correlations between actual and predicted values.

Table 8

<u>Least Squares Regressions Involving DHP Estimates</u>

Dependent Variable	Independent Variables CU	100xT	DCR	DPGNP	R^2
$\hat{\theta}_{cr}$	.010	-2.13		-.031	.824
	(.007)	(0.54)		(.012)	
$\hat{\theta}_{cr}$	.006		-.471	-.016	.967
	(.003)		(.036)	(.005)	
$\hat{\theta}_{kq}$	.039	-5.71		.060	.743
	(.011)	(0.86)		(.019)	
R^2	.043	-7.76		.025	.961
	(.011)	(.049)		(.011)	

Note: Dependent variables are estimates reported by Domowitz, Hubbard, and Petersen (1986, Table 2). The sample period is 1958 -- 1981. Figures in parentheses are standard errors.